

Self-organized control for musculoskeletal robots

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June 16, 2016

Abstract

With the accelerated development of robot technologies, optimal control becomes one of the central themes of research. In traditional approaches, the controller, by its internal functionality, finds appropriate actions on the basis of the history of sensor values, guided by the goals, intentions, objectives, learning schemes, and so on planted into it. The idea is that the controller controls the world—the body plus its environment—as reliably as possible. However, in elastically actuated robots this approach faces severe difficulties. This paper advocates for a new paradigm of self-organized control. The paper presents a solution with a controller that is devoid of any functionalities of its own, given by a fixed, explicit and context-free function of the recent history of the sensor values. When applying this controller to a muscle-tendon driven arm-shoulder system from the Myorobotics toolkit, we observe a vast variety of self-organized behavior patterns: when left alone, the arm realizes pseudo-random sequences of different poses but one can also manipulate the system into definite motion patterns. But most interestingly, after attaching an object, the controller gets in a functional resonance with the object’s internal dynamics: when given a half-filled bottle, the system spontaneously starts shaking the bottle so that maximum response from the dynamics of the water is being generated. After attaching a pendulum to the arm, the controller drives the pendulum into a circular mode. In this way, the robot discovers dynamical affordances of objects its body is interacting with. We also discuss perspectives for using this controller paradigm for intention driven behavior generation.

Keywords: self-organization, robot control, musculoskeletal, tendon-driven, learning, anthropomorphic, self-exploration

1 Introduction

Control is a ubiquitous theme of life and technology. When reaching for a cup of coffee or walking through the mountains, our neural systems control all movements with great ease, despite the great uncertainty involved in controlling the muscles, the complexity of the task and many other factors. That this simplicity is an illusion is seen as soon as trying to program a robot for doing a task. While the complexity of programming stands as a challenge for decades, in recent times considerable progress has been achieved by new ma-

terials [11], powerful actuators [27], the improved theory of control [30], but in particular by the tremendous increase in computational power that allows modeling and physically realistic simulations of very complex systems to improve planning and control [6, 17, 24] and even allows to simulate large controlled muscular body systems [35], or find new perspectives for artificial evolution [2] by exploiting super computer power. However, any approach setting on computer power finds its boundaries promptly by the combinatorial complexity of robots in the environment. The DARPA challenge presents numerous examples of progress but also reveals a realm of failures of these systems even under remote control. Also there are a variety of new control paradigms around, best demonstrated by the amazing locomotion abilities of the Boston dynamics robots, like BigDog, PETMAN and others. These are ingeniously engineered systems for realizing a specific set of tasks with their highly specialized bodies.

The present hype in “classical” robotics evokes the early times of AI with its firm belief that the behavior of robots can be prescribed on a formal level by formulating a set of rules to be realized by the machine. In practical applications, this approach proved very soon to fail due to the complexity of both modeling and controlling real world scenarios. A rethinking began more than two decades ago, with Rodney Brooks statement “the world is its own best model”, prompting a drastic change of paradigms in the control of autonomous robots [3, 4]. The so-called embodied AI recognizes the body as an equal partner in the control process. The exploitation of the specific properties of the body, sometimes called *morphological computation* [10, 19, 21] has subsequently become an active field of research with many impressive results, see [20, 22] opening new perspectives for both robot control and our understanding human sensorimotor intelligence [23].

To date, the two branches of robotics—the classical AI versus the embodied approach—coexist, each one having its realm of relevance. The embodied approach seems to be favored in systems with strong physical effects, like soft robotic systems or elastically actuated robots, where the engineering approaches run into severe difficulties. The limitations of present day engineering approaches to human like structures is best seen when considering muscle-tendon driven (MTD) systems where an important line of research was shaped by EU projects leading from CRONOS, to ECCEROBOT to MYROBOTICS, but also by Japanese projects creating the

highly sophisticated Kenshiro robot [12, 18]. While excellent work has been done in planning, constructing, and eventually building these robots [33], the control of these systems [18, 25, 26] is still in its infancy. Problems stem from the fact that every movement leads to a whole body answer and the effect of an action has much different effects depending on the state of the system. One option is to model the system in order to map it to a conventional rigid joint system, with workspace analysis [14] and actuation effects computed by a suitable cable routing matrix approach [13]. However, measuring joint angles precisely is a problem in practice and also to account for tendon/muscle elasticities causes severe inaccuracies especially when it comes to dynamics.

The other option is to use learning to achieve a new behavior, e. g. with reinforcement learning. For this a suitable exploration has to be implemented, because a random unstructured search is not feasible. We argue that a new control paradigm based on self-organization can bootstrap the control problem by providing basic dynamic behaviors in a very short time, which can be later combined to solve tasks by known learning methods. The idea of self-organizing behavior is quite different from classical control because there is **no** target signal or any other specific input to the system. The only source of information are the sensor values itself, containing the responses of the world to action on which a suitable generic drive has to be implemented. In this work we propose a generic drive that increases velocity correlation between the degrees of freedom. The concrete new behavior emerges from old behavior in a dynamical process where the classical roles of the controller and the controlled are seemingly inverted. This paper demonstrates that a controller, only given in terms of responses of the world without a predefined goal, leads to self-organized control producing a wealth of meaningful behavior in embodied robotic systems. The paper also outlines some of the most prominent consequences. Our approach somewhat implements the idea of Pfeifer and Bongard [20] that “the body shapes the way we think” directly into a low-level control framework, letting the body become actual creator of the robot’s basic way of acting and eventually thinking.

There are also other approaches for creating self-driven behavior from generic drives. There is predictive information maximization [16] which creates less coordinated behaviors than the presented approach, but is similar in the setup. Active goal exploration [1] can be considered as an implementation for high-dimensional systems of the long suggested maximizing of learning progress [29]. It was not yet applied to soft robots, requires a much longer time for new behaviors and is not interactive. However, it results in a complex internal model of the robot which we do not train here.

For our experiments we have chosen an anthropomorphic musculoskeletal arm-shoulder platform that is actuated by tendon-spring elements. This robot has many degrees of freedom (10) and is elastically actuated which makes it hard to be classically controlled. We demonstrate that our control approach creates a meta-system—formed by controller, body, and environment—with a rich variety of all kinds of attractors. These can be deliberately switched by manipulative disturbances, creating an attractor meta-dynamics [9]. We

use the same controller without any changes for all experiments. There is no reward or specific goal, just the responses of the world (sensor values) which guide the behavior by the generic drive to increase velocity correlations between the joints. This is seen by the “willingness” of the meta-system to follow and repeat manually imposed motion patterns. More interestingly, the meta-system may become a resonator which is excited by the self-amplification of latent motion patterns of its physical subsystems. For instance, when suspending a weight from the tip of the arm, the meta-system is piloted by this pendulum into a resonant state where the pendulum weight describes a circular motion pattern. Different from a chain carousel which is driven by an outside torque, this motion pattern emerges only by the self-amplification of the tiny but systematic forces exerted by the pendulum on the muscles of the arm. In another setting, when given a bottle half-filled with water, the robot starts shaking the bottle in a definite manner, driven by the dynamics of the water.

These and many more behaviors can be observed in a single run, without stopping the system or manipulating the controller in any way, and is a direct consequence of using the physical responses as the only source of information. This work is a further development of our previous work [5], putting the approach on a more solid theoretical basis and demonstrating its usefulness with a really challenging physical system. We also discuss perspectives for using this controller paradigm for deliberate behavior generation. This is the decisive next step that will leverage the approach to a versatile tool for behavior generation of soft robots.

2 Self-organized control for soft robots

The controller, we propose, is a function that receives at time t a vector of sensor values $x_t \in \mathbb{R}^n$ and sends a vector of motor values $y_t \in \mathbb{R}^m$. As we aim at self-organization of control, we have to define the control signals in a self-consistent way on the basis of the history of sensor signals alone. Let us introduce $x'_t = x_{t+\theta}$, the vector of the future sensor values, where θ is a time lag with $\theta = 1$ in the derivations given below (time is measured in discrete update-steps, here up to 100/sec).

In order to have non-trivial behavior the sensorimotor loop needs to be mildly destabilized, driving it into self-excited behavior modes. In this sensorimotor loop the controller regulates the energy feed-in. Destabilization can be achieved by increasing the overall feedback strength. However, to keep this destabilization in bounds, we need a conservative element which is formulated by the following self-consistency requirement. We postulate the existence of a forward model given by the (state dependent) matrix A so that

$$x'_t = A_t y_t + \xi_t \quad (1)$$

where ξ is the modeling error. This describes the physical dynamics over one time step. Introducing M which is the inverse or pseudoinverse of A we require y to be a function of the future sensor values x' ,

$$y_t \stackrel{!}{=} M_t x'_t \quad (2)$$

This is the conservative element as it binds the control of the system and hence the energy feed-in to the real physical situation. So, Equations (1) and (2) display the essential idea of our approach to make motor signal compliant with the world dynamics. In a sense, Eq. (2) means that the world’s responses, represented by x' , signals the controller what to do. But of course the world (i. e. the future sensor values x'_t) is also controlled by the controller through the actions y (1).

The choice of the sensor-to-motor mapping M will be discussed below, see Sect. 5.2. However, it only has to capture the coarse causal relationship between sensor and motors and even in the case of the tendon driven robot a one-to-one mapping is used (M is the identity matrix) because each motor position is related to the tendon length on a one-to-one fashion. In this way Eq. (2) boils down to $y_t \triangleq x'_t$.

However, we cannot use Eq. (2) directly for generating the control signal y as it contains the future. So, we must find a model for relating the future sensor signals x'_t to their past, i. e. x_t, x_{t-1}, \dots . In other words, we need a time series predictor for the sensor dynamics. This may be obtained in many different ways, however, we propose one that is particularly simple and creates a general drive to increase velocity correlation between the degrees of freedom, see also Appendix Sect. 5.1. It consists of a time varying linear predictor for the derivatives of the sensor values in the form $\dot{x}'_t = \bar{L}\dot{x}_t$. The matrix \bar{L} is given by an exponential weighted time average of the past velocity correlations as

$$\bar{L}(t) = 1/Z \sum_{s=0}^{t-1} \rho^{t-1-s} \dot{x}'_{t-s} \dot{x}_{t-s}^\top / \|\dot{x}_{t-s}\|^{-2}, \quad (3)$$

where $\rho < 1$ and Z is a normalization constant. The important part is the term $\dot{x}'_{t-s} \dot{x}_{t-s}^\top$ measuring the velocity correlations between sensor vectors with a given time lag. The predictor \bar{L} is then used in the following controller

$$y_t = g(C_t x_t) \quad (4)$$

where $C = M\bar{L}$ (all quantities at time t). The function $g : \mathbb{R}^m \rightarrow \mathbb{R}^m$ is a squashing function so that motor values are kept in bounds. In the applications we use the tanh function applied element-wise. Note that the matrix C can also be obtained from an update rule, see Sect. 5.5, which differs from earlier work [5] by the normalization factor $\|\dot{x}\|^{-2}$ in Eq. (3). In the experiments this leads to a more continuous activity in the behaviors avoiding long pauses of inactivity.

The self-consistency principle formulated by Eq. (1)–eqn:controls is not yet operational. There is a global attractor given by $y_t = 0$ for all t (note that the squashing function g is antisymmetric), i. e. in a position controll setting all actuators are in their central position given by $y = 0$. In order to destabilize this attractor, we use that the sensorimotor system is a feedback loop with the controller regulating the energy feed-in. For increasing the overall feed-back strength, we replace the matrix elements of C in Eq. (4) as $C_{ij} \leftarrow \kappa C_{ij} / (\|C_i\| + \lambda)$, with $\|C_i\|$ denoting the norm of row i and $\lambda \ll 1$ is a regularization for keeping the normalization factor in bounds. κ may be considered as a kind of “character” parameter as it defines essentially the amplification factor of the loop. Using $\kappa > \kappa_c$, where $\kappa_c \approx 1$, it

determines the amplitude of the emerging motion patterns. A second such “character” parameter is given by the time scale ρ for the history of the sensor values included in C , see the Appendix for details. The implementation of the controller is thus simple and boils down to just two equations Eq. (3) and Eq. (4) with the normalization of C described above.

This controller paradigm differs from usual paradigms in many ways. There is no specific goal, no target signal, no learning, no biasing, no sampling, and no preprocessing or preconditioning. There are just the two “character” parameters ρ and κ . All the controller does is to push incoming sensor vectors into the history stack and use the latter for evaluating C . Why is such a simple controller able to generate the different behaviors by itself? When considering \bar{L} we see that it basically contains the *velocity correlations* of subsequent sensor vectors in the recent past such that the system is driven towards patterns with high velocity correlations in the sensor values. Any initial movement or perturbation sets the germ for a small movement which is then amplified due to the positive feedback strength set by κ , if sufficiently large. However, an unbounded growth of the motor values is not possibly due to the non-linear controller (g function) which leads to a confinement. A solution to the requirement of maintaining high velocity correlations and a positive feedback loop is to enter an oscillation. The orbit of the limit cycle is however strongly influenced by the velocity correlation which are determined by the embodiment effects. Behaviors become stationary if they fulfill the *self-consistency* where \bar{L} given by Eq. (3) produces with the behavior which sustains L . This is the case for harmonic oscillations where \bar{L} become more or less a constant rotation matrix. However, also a limit cycle in the L dynamics is possible leading to a periodic change in the behavior. Until a stationary behavior is found the system wanders in a long transient through many different oscillatory behaviors, in some cases this process may not end because no self-consistent behavior is found. A deeper mathematical analysis is left for future work.

The essential feature is the irreducible unity of the controller and the controlled in an adaptive self-referential dynamical system – a meta system. The idea to consider the sensorimotor loop as a closed meta-system is also central to a body of work, see for instance [8, 28, 31, 32].

3 Experiments

The above defined controller was used in the experiments with a tendon driven arm-shoulder system from the Myorobotics toolkit [15], see Fig. 1. The system has 11 artificial muscles, 8 in the shoulder and 2 in the elbow and one affecting both. However two of the shoulder muscles were disconnected. The muscles are composed of a motor winding up a tendon connected to a spring, see Fig. 1(b). The length of a tendon l is given by the motor encoders and the spring force is translated into a length s in the interval $[-\alpha, 1 - \alpha]$ where α defines pretension (here $\alpha = 0.1$). The length of the tendons is normalized to $l \in [-1, 1]$. We define the sensor values as

$$x_i = l_i + \beta s_i \quad (5)$$

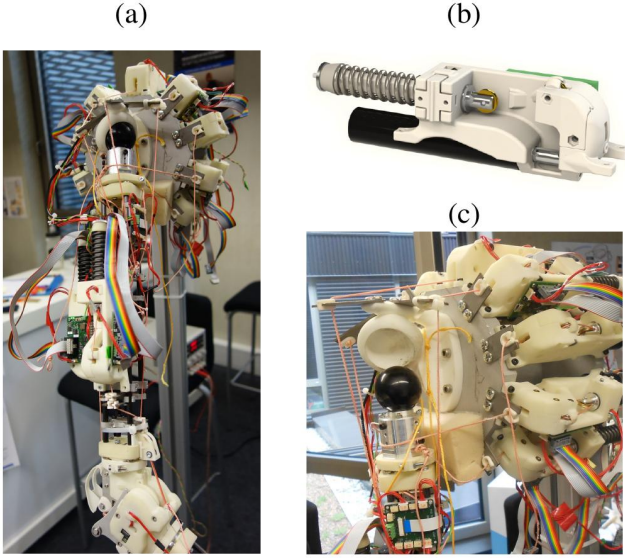


Figure 1: **Myorobotic arm (a), a single muscle element (b), and a dislocated shoulder (c).** The dislocation happens wickedly as soon as the tendons are getting slack.

where β regulates the integration of the spring-length. In the experiments, β was simply set to 1 without further tuning. It is expected that this choice is not critical.

3.1 Peculiarities of muscle-tendon driven systems

There are a number of features which make the muscle-tendon driven (MTD) systems different from classical robots having revolute joints with direct motor control, i.e. the motor positions directly translate into joint angles and into poses. The most obvious effect is seen when tendons are getting slack so that contact with the physical state of the arm is lost altogether. This has to be avoided by keeping a permanent tension on the tendons, which poses another problem: The tension can only be achieved by tightening each tendon up against all the others, each individual tension being reported by the spring length. This means that (i) there are infinitely many combinations of tension forces for a single arm pose and (ii) that the action of a single motor will be reflected in a change of spring length of all other muscles. In other words, actuating a single muscle is reflected by a pattern of sensory stimulation—a whole-body answer.

Furthermore, the combination of friction effects and muscle-pose ambiguity leads to a strong hysteresis effect. After driving the arm by a sequence of motor commands from pose A to pose B one ends up in a different pose and muscle configuration than A after moving back by reversing the motor commands. In general, this makes the translation of a kinematic trajectory for the arm into motor programs extremely difficult, even more so if there are loads and high velocities involved. Also, the classical approach of learning a model by motor babbling becomes illusory. In a sense, these problems dissolve partially when using the system’s physical responses for finding the control signals.

3.2 Self-regulation, manipulability, and goal orientation

We conducted several experiments listed in Tab. 1 which demonstrate the essential features of the control scheme. All experiments are done with the same controller with the same initialization ($C = 0$) so that it is only the physical situation that differs between the experiments. We will keep this paper mainly on the level of phenomena, providing a deeper analysis in a later paper. We recommend consulting the videos for better understanding.

3.2.1 Self-regulated working regime

Before presenting the experiments in more detail, let us take a look at the sensorimotor coupling that is created by this controller. One of the crucial features is the self-regulation into a working regime where the tendons are kept under tension even in very rapid motions with notable loads. This is very important as it guarantees the signals from the controller to be executed in a definite way. As a result, in all experiments we never had to face a shoulder dislocation, see Fig. 1(c), which may happen promptly if tendons are getting loose. This is the more astonishing as this sensible working regime emerges without any additional tuning or calibrating [34] the system. For that, the particular sensor configuration Eq. (5) seems to be important, but we did not study it systematically yet and expect other configurations to work as well.

3.2.2 Manipulability

The dominance of the sensor responses in the control framework makes the controlled system manipulable by externally applied forces. The point is that any additional forces applied to the arm segments change the sensor values via the changing spring tension. This effect integrates manipulative influences—like a physical robot human interaction—into the sensor values and thereby, via the controller matrix C , in the behavior generation. For instance, the arm can always be stopped by applying a force by hand. The reason is not that the motors are too weak. Instead, $\dot{x} = 0$ is a fixed point of the dynamics the meta-system to which it relaxes if the mechanical degrees of freedom are frozen manually¹.

Moreover, the system can be entrained by manual interaction into specific behaviors. We demonstrate this in the handshake experiment, see Video 2, where the user is trying to move the arm in a periodic pattern. Besides the possibility to train a robot in this way, the most interesting point is the subjective feeling that comes about when interacting with the robot. In the beginning of such an interplay, the robot seems to have a will of its own as it resists the motions the user is trying to impose. But after a short time the robot follows the human more and more and eventually is able (and “willing”) to uphold the imposed motion by itself. Otherwise, depending also on the human partner, the meta-system of robot and human may “negotiate” a joint motion pattern which might be left if the human quits the loop. This can be understood

¹This effect involves the normalization factors and fades away once the regularization comes into play. After that, the system tries to move to the global attractor $\dot{x} = x = 0$.

Table 1: **Experiments.** The videos can be watched at <http://playfulmachines.com/MyoArm-1>. An overview is given by a cut version in Video 1.

| Title | Description | Sect. | Vid. |
|--------------------|---|-------|---------|
| Handshake | Human robot interaction by manually imposing a periodic movement | 3.2.2 | Video 2 |
| Bottle swing | Suspending a weight from the tip of the arm: excitation of a circular pendulum mode | 3.3.1 | Video 3 |
| Shaking horizontal | A quarter filled bottle is horizontally attached to the tip of the arm: shaking of the bottle mainly along its axis | 3.3.2 | Video 4 |
| Shaking hori. II | Second example of the horizontally bottle case with more liquid | 3.3.2 | Video 5 |
| Shaking vertical | The same as above but with vertical attachment | 3.3.2 | Video 6 |
| Free | No external forces applied: pseudo-random sequences of reaching-type behavior | 3.4 | Video 7 |

by realizing that many periodic patterns are consistent with Eqs. [4, 8]. If the imposed patterns matches one of them then the robot is controlling this pattern by itself. In fact, in the experiments, one can well observe that a “compliant” human is intrigued to follow the system as much as its own intentions, ending up in an orchestrated human-machine dynamical pattern.

The training of a robot by directly imposing motions is not new. The common approaches generate a kinematic trajectory which is afterwards translated into the motor commands by well known engineering methods. We argue that this method will run into severe difficulties due the peculiarities of our MTD system as discussed in Sect. 3.1. On the contrary, in our approach we have an entrainment effect in the meta-system (body plus controller) which does not need kinematics and dynamical modeling at all.

3.2.3 Perspectives for goal oriented behavior

Another aspect is given by the challenging task of deliberate control, like realizing a given behavior. Let us consider the perspectives of our approach for that task. The idea is based on the observation that the meta-system (the physical system with the controller regulating the energy feed-in) has totally different physical properties than the “bare” or passive system (motor power switched off). In particular, with $\kappa \approx \kappa_c$, self-amplification is subdued so that the meta-system goes into a plastic aggregation state. In this specific regime, patterns are present as mere potentialities waiting to be excited. It is easy to conceive that through a second controller—let us call it the meta-controller—acting on the meta-system, it is more reliable to drive the meta-system toward those latent behaviors than by acting on the “bare” physical system. In fact, if we are able to influence the meta-system by hand, why not by just superimposing additional motor signals on the self-regulated meta-system. The use of the approach is encouraged by the mentioned ability of the meta-system to uphold a resilient working regime (see above) even under extreme external perturbations, preventing, for instance, shoulder dislocations.

3.3 Emerging modes

As mentioned already above, with the transition operator \bar{L} , the meta-system is particularly akin to periodic motions, i. e. there is a plenitude of latent limit cycle attractors which, metaphorically speaking, wait for their excitation. The selection of a specific attractor is realized by the self-amplification

of a dynamical seed, generically provided by a physical subsystem (of the world) with a time coherent internal dynamics. In other words, the subsystem—by its internal dynamics—is piloting the meta-system into a resonant state, i. e. a whole-system mode with defined frequency. This salient phenomenon is a direct consequence of giving the world the leading role in behavior generation. In the following experiments, we additionally feed in delayed sensor values which enhances the affinity for periodic behaviors, see Sect. 5.3.

3.3.1 Self-excited pendulum modes

In a first experiment, we suspend a weight (the bottle) from the tip of the arm. The world in this experiment consists of the arm together with a physical subsystem—this pendulum—with a complex internal dynamics. With the pivot point at rest, the pendulum may realize ellipsoidal or even circular motion patterns with fixed frequency. With a driven pivot the pendulum is able of chaotic motions under certain trajectories of the pivot point. In any case, the motions of the weight exert small forces on the arm which change the spring tensions and thereby the sensor values. While being tiny, these reactions are systematic so that they may accumulate in C_{ij} . The emerging pathways in the feedback loop sensitize the meta-system to potential pendulum modes, readying itself for their self-amplification.

In Video 3 it can be seen how latent velocity correlations are being amplified to end up in stable circular motion patterns of the weight. The experiment starts in a situation where the motor activities have settled to rest, interrupted by occasional bursts so that the bottle is excited to some minor pendulum motion. The thereby induced elongations of the springs induce the said self-amplification of latent pendulum modes as observed in the experiments, see also Fig. 2. These findings corroborate our claim that the subsystem—by its internal dynamics—is piloting the meta-system into a resonant state, i. e. a whole-system mode with defined frequency. This is also supported by the data recorded from the experiment. When analyzing the time lag between measured force and driving signal (motor commands), see Fig. 3(a), it becomes evident that initially bottle and arm are not in a fixed phase relation. During that interval, the structure of the controller matrix C changes strongly until the system reaches the rotational mode, see Fig. 3(c). This illustrates the dynamics of the controller to find a self-consistent behavior. Without perturbation this oscillatory behavior may become stationary. However, later in the experiment the string of the pendulum was shortened such that a different sensorimotor coordina-

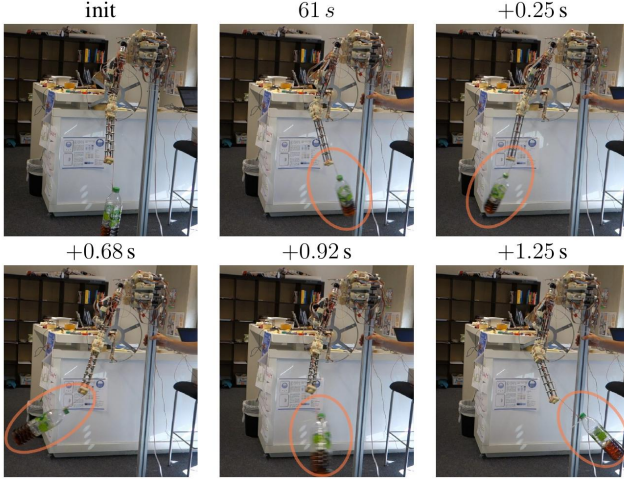


Figure 2: **Swinging the bottle.** Still images of Video 3.

tion forms. An indicator that the oscillations are produced by the controller is found in the complex eigenvalues of the linearized internal dynamics \bar{L} as displayed in Fig. 3(b). During the swinging mode, we find only 1 pair of significantly non-zero complex eigenvalues representing the main oscillatory component. This confirms our observations that low-dimensional behaviors emerge.

3.3.2 The emerging cocktail shaker

In a next series of experiments we attached a bottle filled with some water to the tip of the arm in either horizontal or vertical orientation. These experiments are meant to support our hypothesis that the meta-system may become resonant with the internal dynamics of a subsystem, if the latter provides correlations over space and time. This internal dynamics is making itself felt by the inertial forces when the water is hitting either the walls or top and bottom of the bottle. These impacts cause a reaction of the springs and hence of the sensor values. This may increase correlations in \bar{L} , which enhances motions of the arm in coherence with these signals.

This hypothesis is difficult to analyze by the data alone, but we can get an impression by changing the physics of the subsystem. In a first step, see Video 4, the bottle is filled only with a little water so that the reactions of the subsystem are weak. Nevertheless, the meta-system is already reacting to the motions of the water inside the bottle, but the emerging modes are only metastable² with a very short life time. Each mode is followed by a short irregular regime until a new short-lived mode emerges through the interplay of the arm movements and the water.

In the next step, the bottle is half-filled so that the reactive forces are much stronger. In both Video 5 and Video 6 the modes are more pronounced and live much longer. In Fig. 4 we present the time series data for the horizontal case. One can see how from the initial resting position the arm starts to move until, after about 25 seconds, it reaches an oscillatory mode involving strong sensor reactions (increased by the acting forces). Interestingly, the modes are not only realized

by the arm and the attached bottle but involve also the reactive motions of the post the arm is mounted on (see video). The latter point can be seen if the post is fixed by hand in order to stop its swaying motion. Then, in both videos, it can be seen that the mode breaks down immediately. Obviously, the mode involves both physical objects the arm-shoulder system is attached to. This is not a surprise, as this system, by its dynamics, exerts forces on both the bottle and the post leading to correlated changes in spring tensions and sensor values. This effect is also seen in Fig. 4(b,d) where shortly after second 40 the eigenvalues change and the C matrix changes until it reaches about the same configuration at second 50. As seen already at the handshake experiment, the arm can always be manually stopped and the behavior can be changed. At second 79 the arm was stopped and brought to rest. After the release 3 seconds later a different mode appears, c. f. the changed motor pattern in Fig. 4(a) and the different C matrix in (c). To conclude, the dynamics of the C matrix (4) is typically on a long transient (Fig. 4(d)) until it hits a self-consistent behavior. Any perturbation or change in conditions leads to an adjustment of the controller and the behavior always aiming for a mode where high velocity correlations appear.

3.3.3 Discovering object affordances and tool use

The observed resonance phenomena have a close relationship to the concept of object affordances. As introduced by Gibson [7], affordances are action possibilities available in the environment to an individual. Depending on its action capabilities, affordances define the relation between an agent and its environment through its motor and sensing capabilities (e.g., graspable, movable, or eatable). In this sense, in the same way as a chair affords sitting or a knob affords twisting, we may say that the meta-system discovers the possibility to drive the attached pendulum into a circular motion by moving the pivot in a definite way. This is one affordance a pendulum can offer in that specific setting. Interestingly, this discovery can only be made by the emerging whole-system activity with the pendulum on the basis of the very weak interactions in the arm-pendulum physical system. In the same sense, when giving the robot the half-filled bottle, through the response (by the inertia forces) of the water to the taken actions, the meta-system discovers shaking the bottle as one possible affordance. We expect that with different objects the meta-system may discover further affordances like the turning of a wheel as already observed in a simulated system, see Der and Martius [5].

Object affordances may form pre-requisites for prediction and planning and are important steps in the emergence of tool use up to generalization, abstraction, and even creativity in cognitive robots. We hope to support these ideas with our next experiments with the arm-shoulder system.

3.4 Reaching

The functionality of the present control paradigm essentially rests on two different scenarios. On the one hand we have seen a strong affinity for periodic motions like the pendulum or the bottle shaking modes. These are predominantly

²We borrow the term metastable from physics, meaning a mode with a limited life time.

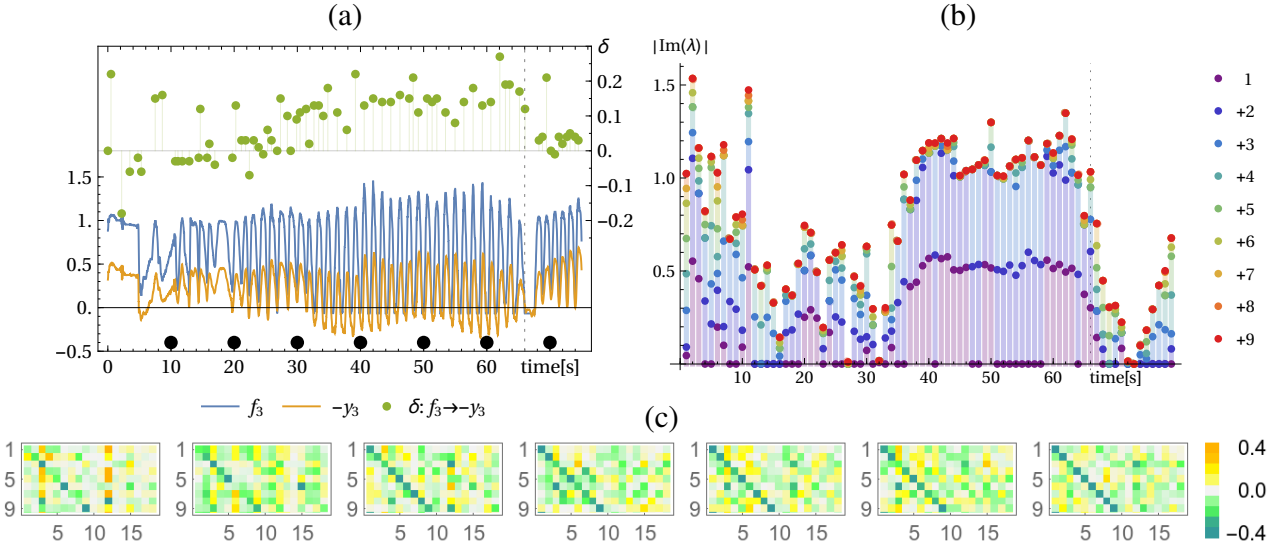


Figure 3: **Bottle swing experiment.** At second 66 the string of the bottle was shortened, see Video 3. (a) Force sensors and control signal of muscle 3 and their time lag. The measured force (spring compression) and the control signal y (desired tendon length) follow a similar trajectory with inverted sign (note $-y$). The time lag δ (right axis in seconds) between force and motor value (same result for other muscles) indicates that initially the control and the environmental influences are not in sync whereas in the swinging mode (from 33 s on) a stable phase/time-lag relation is observed. (b) Displayed are the absolute imaginary parts of the eigenvalues of the linearized system dynamics (Jacobian \bar{L}) (averaged over 1 s) and cumulatively plotted (1, 1 + 2, 1 + 2 + 3, ...). During the pronounced oscillation between 35 and 68 sec there is one pair of dominant complex eigenvalues. (c) Corresponding controller parameter C at the seconds 10, 20, ..., 70 (from left to right) as indicated by the black dots in (a).

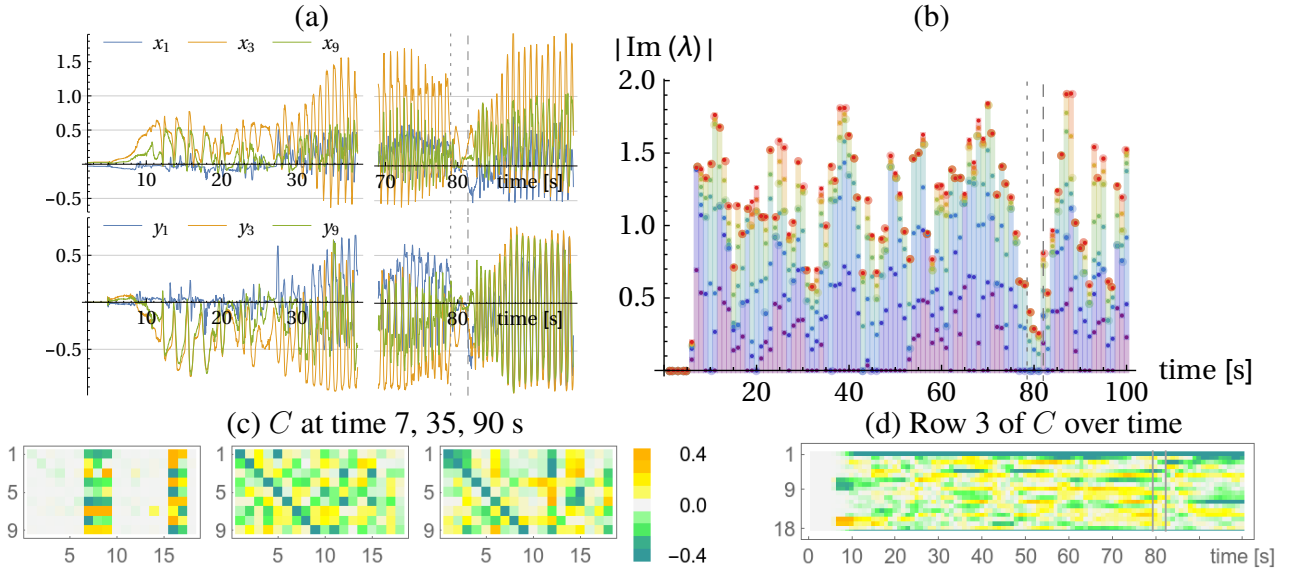


Figure 4: **Horizontal bottle shaking experiment.** The system starts at $C = 0$ at time 0. At second 79 the arm was stopped and then released at second 82 (indicated by vertical lines), see Video 5. (a) sensor values (x) and control signals y of muscle 1, 3, and 9. (b) Displayed are the absolute imaginary parts of the eigenvalues of the linearized system dynamics (Jacobian \bar{L}) (averaged over 1 s) and cumulatively plotted (1, 1 + 2, 1 + 2 + 3, ...). We find one pair of dominant complex eigenvalues accompanied by a second less strong pair. (c) Corresponding controller parameter C at the seconds 7, 25, ..., 90 (from left to right). (d) The evolution of the coupling to one muscle (3) over time (corresponding to row 3 in C).

observed with time scales, defined by ρ , of the expected periodicity. There, we observe that the dynamical operator \bar{L} is essentially constant and is qualified by (a pair of) complex eigenvalues determining the frequency of the oscillations.

With other time horizons, either shorter or not matching the period of a latent mode, we observed another amazing variety of behavioral patterns which give the impression as if the robot deliberately generates sequences of different poses, see Video 7. This scenario is characterized by a \bar{L} that is strongly varying on the time scale of the behavior itself. Though these sequences of movements look rather random, it is important to note that there is no artificial randomness implanted in the controller. Instead, the controller is an explicit deterministic function of recent sensor values. So, we have a pseudo-random behavior with a strong bias caused by the physical properties of the meta-system.

Noteworthy, despite their pseudo-random character, these patterns are fully controlled as they are determined by their recent history in sensor space. So, a pattern can be reproduced by starting the system with the history recorded in an earlier experiment. In this sense, motion patterns are reproducible and may be used in higher level functional architectures. In particular, this is of interest for generating behavior architectures of the arm like realizing a predefined trajectory or reaching toward a specific point. We strongly believe that this property can open new ways for controlling such complex systems, bypassing the need for modeling and concrete programming the behavior of the robot following the common paradigms of control.

4 Summary and outlook

This paper discusses a novel approach for controlling systems with strong embodiment effects. Instead of using specific goals or targets we aim at behavioral self-exploration of the system under control. Desired behaviors can then be generated on top of such basic behavioral primitives. This is in contrast to the typical control approach where specific goals have to be met in an optimal fashion. For elastically actuated robotic systems, however, we are lacking analytical models and often have no direct way to specify a desired behavior, except as reward and punishment signal in reinforcement learning but this takes prohibitively long in the systems considered here. Our approach creates behavior only based on the responses of the system in the most recent past in an online fashion. The essential new feature is the irreducible unity of the controller and the controlled as formulated by the pair of Eqs. [1, 2]. The controller is devoid of any system-related functionalities as it is given by a fixed, explicit and context-free function of the recent history of the sensor values (3). In this interplay between the controller and the controlled, fuelled by the positive feedback strength, the controller manages to identify and amplify tiny responses from the world outside itself. In our case study with the tendon-driven arm shoulder system, if the arm alone will realize a seemingly pseudo-random but fully controlled sequence of poses. But more interestingly, if the arm is extended by attaching objects with an internal dynamics of its own, the controller gets in a functional resonance with the object's internal dynamics:

metaphorically speaking, with a half-filled bottle the system develops into a cocktail shaker and after attaching a pendulum to the tip of the arm, the controller, mediated by the arm, drives the pendulum into a circular mode.

All these patterns emerge with great ease and in a natural and elegant way starting with $C = 0$ as initial condition. The novelty of this approach can be expressed by the simple argument that comparable motion patterns can only be generated with existing controller paradigms if a great amount of knowledge about the system is available or after very long training times with handcrafted reward schemes. Remember that the controller receives nothing but the sensor signals—the sum of tendon plus spring length, so the result is highly non-trivial. Moreover, we have also given perspectives of how to extend this controller paradigm to goal oriented behavior by just superimposing additional motor signals on the self-regulated meta-system in its “plastic aggregation state”. This promises a qualitative leap in controlling such robotic systems.

As a perspective, the observed response of the system to the world's internal degrees of freedom—as demonstrated with the pendulum, e. g. —leads the way to an important generalization: equipping the robot with additional sensors reporting the spatial relation of its mechanical degrees of freedom to the structure of the environment, we expect a similar integration of those relations into the emerging behavioral modes. In a preliminary experiment, by integrating a camera this mechanism even lead to an active exploration of visuo-motor coordination.

Finally, let us discuss on which platforms our controller is likely to create useful behavior in some way or the other. First of all, the system has to provide sensory feedback about acting physical forces to make embodiment effects perceivable by the controller. This is, for instance, not the case if all perturbations are perfectly compensated by a low-level PID controller. Secondly, there should be sensors reporting a similar quantity as used to control the actuators, e. g. position sensor for position control or force sensors for force control. Additional sensors are typically integrated into the loop if they show a definite response (correlation) to the motor patterns. Thirdly, the behaviors of interest should be oscillatory. Since we only need the main sensor-to-motor wiring information about the particular robot (which can also be learned) and do not any other specific information, we expect our system to work with a wide variety of machines including soft robots, but this remains for future research.

5 Appendix: Methods

In this section we derive the controller matrix C , discuss the role of the sensor to motor mapping matrix M , and give the update rule for C .

5.1 The controller

In order to derive Eq. (4), we need to predict $\dot{x}'_t = \dot{x}_{t+1}$ on the basis of the previous sensor values. Our idea is based on

an operator ³

$$L_t = \dot{x}'_t \hat{x}_t^\top \quad (6)$$

where $\hat{x} = \|\dot{x}\|^{-2} \dot{x}$, which describes the transition $t \rightarrow t+1$ as

$$\dot{x}'_t = L_t \dot{x}_t \quad (7)$$

As to notation, we remark that with any two column vectors a and b , $a^\top b$ is the scalar product and $S = ab^\top$ is a matrix with elements $S_{ij} = a_i b_j$. In particular, $\hat{x}^\top \hat{x} = \|\dot{x}\|^2$ and $\hat{x}^\top \dot{x} = 1$, which corroborates Eq. (7).

Of course, L_t cannot be used directly as it involves the future. The idea is to generalize that expression in a way which is consistent for trajectories with some time coherence. Here, we replace L with its moving average, defined as

$$\bar{L}_t = \frac{1}{Z} \sum_{s=1}^{t-1} \rho^{t-1-s} L_s = \sum_{s=1}^{t-1} p_s \dot{x}_{s+1} \dot{x}_s^\top \quad (8)$$

where $\rho < 1$ defines the time scale for the extension of the past and $Z = \sum_{s=1}^{t-1} \rho^{t-1-s}$ and $p_s = \frac{1}{Z} \rho^{t-1-s} \|\dot{x}_s\|^{-2}$ are normalization and weighting factors, respectively, and we used $\dot{x}'_s = \dot{x}_{s+1}$ in the last step. Writing $x_i(s)$ for the i -th component of the vector x_s and similarly for \bar{L}_t , the matrix elements of \bar{L}_t are

$$\bar{L}_{ij}(t) = \sum_{s=1}^{t-1} p_s \dot{x}_i(s+1) \dot{x}_j(s) \quad (9)$$

and in shorthand $\bar{L}_{ij}(t) = \langle \dot{x}'_i \dot{x}_j \rangle_P^{t-1}$, where $p_s = \frac{1}{Z} \rho^{-s} \|\dot{x}_{s-1}\|^{-2}$ are weighting factors. Note that \bar{L} does not any longer involve the future as it is shifted by one step in time and that the time coherence can be controlled by the decay term ρ . Remembering that $\dot{x}_t = x_t - x_{t-1}$ we see that \bar{L} is given by the history of the sensor values in a definite way.

We may now use Eq. (9) as dynamical operator so that

$$\dot{x}'_t = \bar{L}_t \dot{x}_t \quad (10)$$

generates a time series: given the history $\dot{x}_t, \dot{x}_{t-1}, \dots$, we get the future evolution of \dot{x} by iterating Eq. (10). Note that the history until t defines the future of the time series in a deterministic way so that there are as many time series as there are different histories. Because of this generality, we may call Eq. (10) with Eq. (9) a template defining a certain class of time series. Note there are no parameters involved, apart from the time scale of the history as set by ρ .

Using Eq. (10) we may express the future state \dot{x}' in terms of its history. Taking the time derivative of Eq. (2) yields $\dot{y} = M \dot{x}'$, assuming M is constant. Putting $y = g(z)$ where g is the squashing function, we obtain for the internal control variable z , ignoring the nonlinearity of the squashing function

$$\dot{z}_t \approx C_t \dot{x}_t \quad (11)$$

where

$$C_t = M_t \bar{L}_t \quad (12)$$

In a final step we have to relate \dot{z} to z in a way that is consistent with the postulated slowly varying nature of \bar{L} . In this

paper we use the most simple postulate, i. e. omit the residual time dependence of C altogether. Using the simple relation $x_t = \sum_{s=1}^t \dot{x}_s + x_0$ and analogously for z_t , we define our controller as

$$y_t = g(C_t(x_t - x_0) + z_0), \quad (13)$$

where z_0 is an overall bias that can be set arbitrarily, each z_0 leading to a different control strategy. This versatility is a direct result of working with the \dot{x} . z_0 may also be adapted following a heuristics like avoiding a saturation regions of the squashing function or coping with an overall bias of the system. x_0 plays the role of a sensor bias. In this paper, $x_0 = 0$ as our systems are centered around $x = 0$. Otherwise it can be adapted⁴ similarly to z_0 . In the experiments we used the controller

$$y_t = g(C_t x_t) \quad (14)$$

throughout, where $g_i(z) = \tanh(z_i)$.

For a brief discussion we assume that x_t follows a harmonic oscillation with period T and ask whether this is consistent with the explicit form of \bar{L} as given by Eq. (8). Linearizing Eq. (4) so that $x' = My \approx MCx = \bar{L}x$, we have to consider the role of \bar{L} as applied to x . Considering Eq. (8) together with $\dot{x}_t^\top x_t = \dot{x}_{t-T/2}^\top x_t = 0$ and $\dot{x}_{t-T/4} \propto x_t$, we may argue⁵ that $\bar{L}x_t \approx \dot{x}_{t-T/4}' \propto x_t'$. This crude argument which repeats for each half-period shows that the controller is consistent with the stipulated sensor dynamics, provided the mapping M can translate this into appropriate motor commands. Note also that the time smoothing in \bar{L} does not mean a time smoothed dynamics as the above argument remains valid for any frequency (below the Nyquist frequency for the given update rate).

5.2 The role of M

Central to the approach is the template dynamics Eq. (10). In general, any real dynamics will not fit into that template, i. e. the true dynamics in sensor space generated by the robot can be written as

$$\dot{x}'_t = \bar{L}_t \dot{x}_t + \xi_t \quad (15)$$

where \bar{L} is given by Eq. (9) in terms of the real trajectory as generated by Eq. (15). Let us now hypothetically assume that A represents exactly the sensor response of the arm to the motor actions, i. e. assume $\dot{x}' = A\dot{y}$ with $A = M^{-1}$ and $\xi = 0$. Then, the pair of Eqs. [1, 2] degenerates into a triviality so that the system can realize any trajectory. So, the actual point of interest is the mismatch, represented by ξ , between true behavior and the template. As a rule of thumb we postulate that the controller is able to realize a trajectory the better the smaller ξ . The mismatch ξ directly reflects the physical reactions of the meta-system to the motor actions. In this light, trajectories are more stable for more systematic reactions, involving the degrees of freedom of the physical system in a coherent manner. This is what we may observe in the experiments.

⁴Actually, x_0 is the state at time $t = 0$. However, even by very small perturbations or the residual time dependence of C , the memory of the initial state is soon lost so that we are free to choose the sensor bias.

⁵Note that the norm of the rotating vector is constant and assume $\rho \approx 1$, i. e. the weighting factors p_s are independent of s .

³Actually, L is simply a matrix but we call it an operator for emphasizing the dependence on the states it is operating on.

The standard version is that M is to reflect just the most basic causal relations between sensor and motor signals. M can be learned in simple off-line motor babbling scenarios, see Der and Martius [5] for examples. In this paper, we used the relation between motor encoder and tendon length which is a one-to-one mapping, hence M is the unit matrix (identity operator). This choice also underlines the difference between the matrix M and the usual understanding of an internal inverse model: while the latter is to reflect the mapping from sensors to motors as precisely as possible, M determines ξ —the mismatch between template and true dynamics which determines both the self-exploration rate and the regularity of the generated motion patterns as a (very complex) function of the character parameters (ρ, κ) . More details on this search and converge paradigm may be found in Der and Martius [5].

5.3 Eliciting periodicity

In order to make the meta-system more attractive for motion patterns of a certain period T , we introduce a vector $x_{t-T/2}$ of delay sensor values together with a second controller matrix $C_{t|-T/2}$ and define the vector of the motor commands as

$$y_t = g(C_t x_t + C_{t|-T/2} x_{t-T/2}) \quad (16)$$

where, before normalization,

$$C_{t|-T/2} = M_{t|-T/2} \langle \dot{x}_i \dot{x}_j \rangle_P^{t-T/2-1} \quad (17)$$

and $M_{t|-T/2}$ transforms motor values at time t into sensor values at time $t - T/2$. Note, that $M_{t|-T/2}$ can be different than M_t . If the system is in a periodic regime we have $x_t = -x_{t-T/2}$ and thus also $\langle \dot{x}_i \dot{x}_j \rangle_P^{t-1} = \langle \dot{x}_i \dot{x}_j \rangle_P^{t-T/2-1}$. Choosing $M_{t|-T/2} = -M_t$, we find $C_{t|-T/2} = -C_t$ so that, before the normalization, the argument of the squashing function is given by $C_t x_t + C_{t|-T/2} x_{t-T/2} = 2C_t x_t$. Hence, there is a constructive interference over the half period so that periodic patterns are getting favored for self-amplification. This argument holds true also for any multiple of the fundamental period T .

5.4 Some technical details

In the practical applications done so far, we identified a number of tweaks for coping with peculiarities of the approach. One is the choice of the time lag between x and x' which was $x'_t = x_{t+1}$ above. However, there is no hindrance to introduce a certain lag θ so that $x'_t = x_{t+\theta}$. This is helpful in order to adapt the system to the actual update rate and in particular for enhancing the chance for periodic patterns. It also influences to some extent the frequency of such patterns.

Another point concerns the regularization of the normalization factors which have different effects for either the normalization of C or that of \bar{L} which was introduced with the p_s factors Eq. (9). As the former normalization acts on C directly, its effect is delayed on the time scale given by ρ . The normalization of \dot{x} on its hand also needs some regularization, i. e. we have to replace the factor $\|\dot{x}\|^{-2}$ as

$$\|\dot{x}\|^{-2} \rightarrow \frac{1}{\|\dot{x}\|^2 + r} \quad (18)$$

where r may run in principle from 10^{-1} down to a minimal value determined by the discretization of the sensor values. However, very small \dot{x} are enlarged up to a factor r^{-1} and dominate in this way the definition of C . This is not helpful as in most cases the very small velocities arise from e. g. sensor noise, which tends to destroy the already reached self-amplification of latent behavior. In practice, it is therefore helpful to keep the regularization effect in bounds. In other words, while we were using $r = 10^{-10}$ for this paper, values of $r = 10^{-3}$ seem to work better in current experiments.

5.5 Update rule

We can also give an update rule for C as

$$\tau \dot{C}_t = M_t \dot{x}_t \hat{x}_t^\top - C_t \quad (19)$$

using $\hat{x} = \dot{x} \|\dot{x}\|^{-2}$ or its regularized version given by Eq. (18). With discrete time, we write the update of C as

$$\tau \Delta C_t = M_t \dot{x}_t \hat{x}_t^\top - C_t \quad (20)$$

which becomes stationary if $C = M \bar{L}$.

6 Acknowledgement

We thank Alois Knoll for inviting us to work with the Myrobotic arm-shoulder system at the TUM. Special thanks goes also to Rafael Hostettler for helping us with the robot and control framework. RD thanks for the hospitality at the Max-Planck-Institute and for helpful discussions with Nihat Ay and Keyan Zahedi. GM received funding from the People Programme (Marie Curie Actions) of the European Union's Seventh Framework Programme (FP7/2007-2013) under REA grant agreement no. [291734].

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